The Application of Anomaly Detection Methods in the Robot Industry

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Abstract: This paper reviews anomaly detection systems based on machine learning and algorithms for detecting and quantifying various types of defects in robotic assembly lines. Throughout history, the main method in anomaly detection has been human. By 2000, Artificial Intelligence (AI) is used more and more in anomaly detection. This paper summarizes the deep-learning model, reinforcement learning model, and You Only Look Once (YOLO) Algorithm. Convolutional Neural Networks (CNNs) is a network from deep-learning model which can detect in real-life environments the data given by the camera and sensor. CNNs can perform detection by extracting local features and the space between neighboring pixels. Reinforcement learning uses a technique called Q-learning and also deep Q-networks (DQNs). Q-learning uses the data from previous data set and learns to make choices that optimize long-term returns. This can significantly improve overall efficiency and productivity. Another algorithm mentioned in this paper is YOLO Algorithm also known as the You Only Look Once algorithm. The algorithm collects the data from the image and analyzes the pixels in each image. By using YOLO, the system can optimize the allocation of resources to ensure the correct identification and installation of each component. The research papers show the efficiency and work accuracy of the AI algorithm and machine learning model. The learning process facilitates autonomous improvement of the system.

Keywords: Machine Learning, Algorithm, Anomaly detection

1 Introduction

An abnormal product in industry is one that is defective or does not meet the required standards. In common understanding, abnormal products can damage the reputation and credibility of companies, increase costs and decrease income, loss of market share, etc. Therefore, the companies are dedicated to improving product quality, which is also to decrease the abnormal product rates. By promptly identifying anomalies in the product manufacturing process, it is possible to reduce scrap rates, minimize losses, and mitigate production delays, thereby enhancing production efficiency and profitability. Anomaly detection is the process of identifying deviations from expectations in products, especially those associated with abnormal products, to ensure quality control and operational efficiency. In anomaly detection, Artificial

Y. Wang (ed.), *Proceedings of the 2024 International Conference on Artificial Intelligence and Communication (ICAIC 2024)*, Advances in Intelligent Systems Research 185,
https://doi.org/10.2991/978-94-6463-512-6_25

intelligence (AI) offers many advantages and characteristics that make it ideal for anomaly detection. First, AI can process large amounts of complex data and extract patterns as well as regularities from it. It improves the efficiency of the assembly line and saves labor costs, especially in the U.S. and other developed countries. Second, AI technology can learn and improve adaptively. It increases the accuracy of the detection over time. In addition, AI can quickly respond to new abnormal patterns or trends that happen suddenly which can minimize the loss for companies. Clearly, AI stands out as the key component to improve efficacy, and product reliability and mitigate risks in the anomaly detection.

In industries ranging from manufacturing, robots, and AI are making a big impact worldwide. The example that is closest to us would be ChatGPT which is a type of Artificial Narrow Intelligence (ANI). There are many different types of AI domains such as machine learning, deep learning, reactive machines, theory of mind, and robotics. Each type of domain has more detailed branches. Detecting abnormal products is one specific type of AI that belongs to computer vision and machine learning. Detecting abnormal products was a task for humans in the 1970s and 1980s and earlier [1]. Because of technological improvement, factories have increased production capacity, yet efficiency has not improved. Due to the large amount of data, real-time monitoring with humans is impractical. During the 1990s, humans brought robots into the factors successfully. Real-time intrusion detection systems are able to analyze generated audit data to immediately detect and respond to attacks [1]. During the 1990s-2000s, AI made a big improvement in technology improvement. More analogy detection models have been released. After another 10 years, big data and General Artificial Intelligence became more common in normal human life and business use [1].

Based on the rapid development and significance of this field, this paper intends to provide a comprehensive review of its beneficial advancements. This paper is structured by the following. Section II will detail the implementation specifics of anomaly detection algorithms proposed by other researchers in their research papers. Section III will analyze the current limitations of these methods and suggest future directions for development. Finally, Section IV will summarize the entire paper.

2 Method

2.1. Overview of the Robot Anomaly Detection Model

This paper will review previous research on automated anomaly detection in manufacturing with a focus on identifying defective products on the assembly line. The steps of data collection, feature extraction model construction, model training and testing, and application of the trained model to detect product anomalies will be explained in the following text. 1) **Collect Dataset:** Collect data that is necessary for training. Data include images of products, sensor readings, and quality control logs. 2) **Feature Extraction:** This includes visual features from images, sensor readings, and other measurable parameters that can help distinguish between normal and defective products. 3) **Model Construction:** These models will be capable of identifying deviations from normal product specifications in real time, ensuring that defective items are promptly identified and removed from the production line. 4) **Manufacturing Data Mining:** Develop tasks, procedures, models, and algorithms to analyze data from manufacturing environments and find patterns, correlations, and predictions. 5) **Model Training:** By finding patterns and correlations between features, models learn to distinguish good items from problematic ones. 6) **Model Testing:** Used to ensure that the model correctly identifies faulty items and does not generate a high number of false positives or misses. 7) **Industrial Deployment:** To ensure that only good quality items make it through the production process, it is necessary to incorporate an anomaly detection system into the assembly line.

2.2. Deep Learning for Anomaly Detection in Robotic Assembly Lines

Deep learning has become a powerful tool for anomaly detection in robotic assembly lines. Deep learning models, especially convolutional neural networks (CNNs), are highly effective in these applications due to their ability to learn complex feature hierarchies from raw input data [2]. Deep Neural Network (DNN) consists of an input layer, multiple hidden layers, and an output layer [3] shown in Fig.1. Each successive hidden layer in a DNN learns increasingly complex features from the input data. This hierarchical feature learning enables DNNs to tackle complex problems more efficiently than shallow networks.

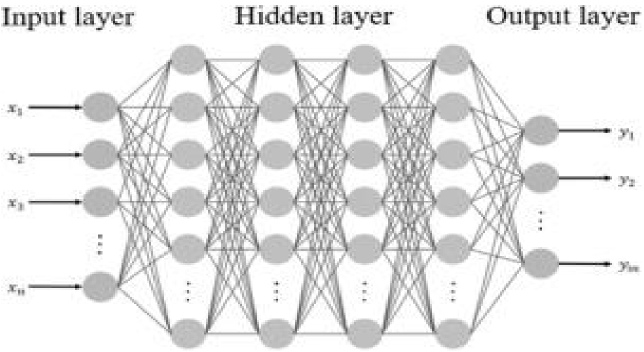

Fig. 1. Layers of DNN [2].

CNNs, a specific type of DNN, are particularly well-suited for image and speech recognition tasks, which are crucial for detecting anomalies in robotic assembly lines. CNNs exploit the spatial correlation between nearby pixels in an image by extracting local features that are then used to detect higher-order patterns and features [4]. This makes CNNs highly effective for processing visual data where local patterns are essential. CNNs have exceptional performance in real-world anomaly detection scenarios.

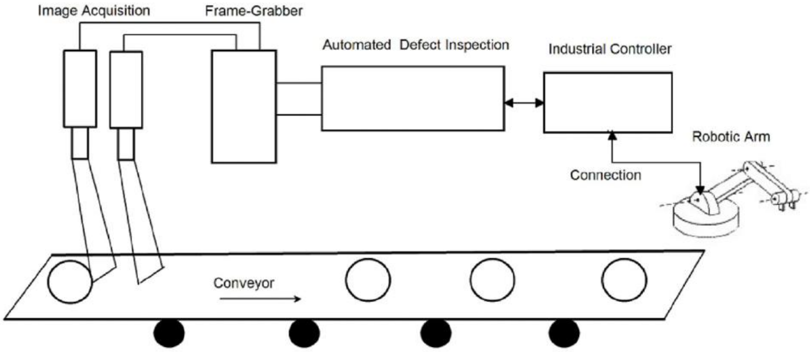

Fig. 2. Automated defect detection workflow [5].

Related work [5] shown in Fig.2: Birlutiu et al. proposed that visual inspection through image processing and analysis is a new technology in a variety of industries, including the global ceramics industry [6]. The International Standard Organization (ISO) has established guidelines for determining the quality of ceramics in the SNI ISO 10545-2:2010 document [7]. The defect measurements specified in the standard include: (i) quality assessment of ceramic surfaces, which covers cracks, crazing, unevenness, pinholes, devitrification glazes, specks or spots, blisters, and welts, and (ii) dimensional measurements, such as length and width, straightness of sides, rectangularity, and surface flatness.

2.3 Reinforcement Learning Based Detection in Robotic Assembly Lines

Robotic assembly line optimization can be achieved dynamically through reinforcement learning (RL). By using information from the assembly line (e.g., production measurements and sensor data), agents in reinforcement learning can learn to make choices that optimize long-term gains. techniques such as Q-learning and deep Q-networks (DQNs) are used to optimize task-ordering and resource-allocation strategies to improve overall efficiency and productivity.

Related work [8]: From the study in the EMSAD system, Q-Learning enhances anomaly detection through historical data optimization. The Anomaly Detection Module (ADM) uses a multi-task learning algorithm to categorize suppliers and predict supply rates. The Learning Decision Module uses this information to determine the best action for the next day. By evaluating state-action pairs and incentives received to continually update Q-values, the system improves its ability to handle anomalies and ensures that energy supply and demand are adjusted efficiently and accurately.

2.4 YOLO Algorithm

YOLO offers a real-time object detection approach. It enables robots to quickly and accurately identify and locate objects, enhancing robotic assembly lines' performance. In the context of assembly lines, YOLO processes visual inputs from cameras or sensors to detect parts and components in real-time. By leveraging YOLO, robotic systems can optimize task sequencing and resource allocation to ensure that each part is properly identified and placed, increasing overall efficiency and productivity.

Related work [9]: From the paper [9], by down sampling the dimensions of the input image by 32, 16, and 8 pixels, respectively, YOLO v3 generates predictions at three distinct scales. The initial detection occurs at the 82nd layer. During the first 81 layers, the image is progressively down sampled by the network, resulting in the 81st layer having a stride of 32. For an input image of 416 x 416, this down sampling produces a feature map of 13 x 13. Detection is then made using a 1 x 1 detection kernel, resulting in a detection feature map of 13 x 13 x 255. [10]. Overall, the paper offers an idea that YOLO v3 shown in Fig. 3 can offer a clear image detection on the frame and make predictions for the data.

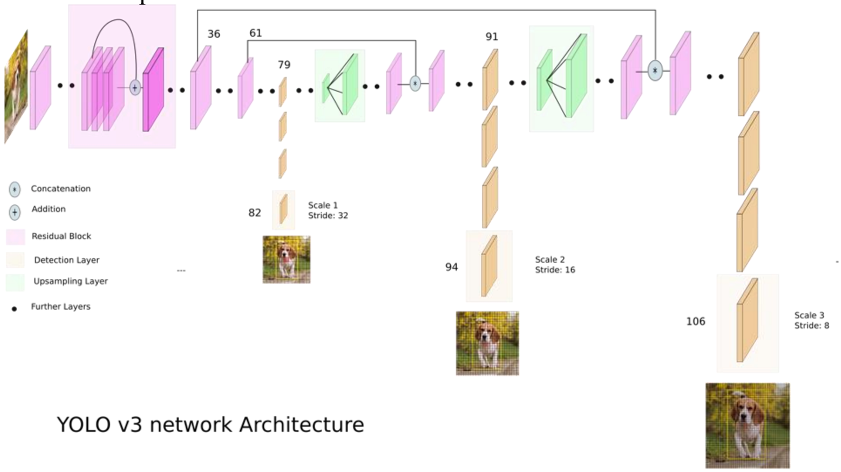

Fig. 3. YOLO v3 network Architecture [10].

The YOLO algorithm treats target detection as a regression problem, using a mean square error loss function with different weights for each component. For the bounding box coordinate prediction error (localization error), a higher weight is used (COORD = 5). For the confidence score of the bounding box without a target, a smaller weight (Anoobj = 0.5) is applied, while all other weights are set to 1 [9]. To account for the difference in sensitivity between small and large bounding boxes, the width and height predictions are taken as square roots. During training, multiple bounding boxes were predicted per cell, but only ground truth IOUs (intersection and concurrency ratios) were used to ensure accurate position prediction.

3 Discussion

The industrial integration of robotics and AI has transformed the way of production. It brings unprecedented productivity, automation, and creativity. Even with the benefits of these developments, controlling and identifying faulty items is still a difficult task.

The difference between deep-learning model and reinforcement-learning model is that deep-learning model excels at identifying patterns in data which helps detect the future. Reinforcement learning is efficient at determining the best path to achieve the goal. Reinforcement learning is simpler, but it is not as good at recognizing patterns as deep learning, which is also more complex and challenging to set up and operate. This paper thinks anomaly detection requires a very high accuracy rate, such as the qualification rate of products, so deep learning will be a better model to apply in anomaly detection. Compared to YOLO, YOLO offers a better analysis on each pixel, but R-CNN tends to achieve higher object detection accuracy compared to YOLO [10].

First, AI is not 100% right in making decisions. AI is like humans; sometimes they will make mistakes. Any mistakes on the assembly line can seriously impact a company's reputation, increase operating costs, reduce revenue, and erode market share. Although upgraded technology, clearer images, as well as accurate data, can prevent large misses, the data might still contain some extreme numbers and might break the algorithms. To address this issue, implement redundant checks using multiple AI models and introduce manual supervision in key procedures.

Second, integrating these systems into existing assembly lines requires seamless compatibility with current processes and machinery, which can involve considerable logistical and technical difficulties. In addition, the systems must be adaptable to changing production environments and scalable to accommodate ever-increasing production volumes, thus requiring continuous updating and maintenance.

Third, cost is another major consideration. Implementing and maintaining a real-time processing system for anomaly detection requires a significant financial investment. This includes the cost of high-performance computing infrastructure, software development, and ongoing maintenance. In order for Robotic Anomaly Detection to be useful, a clear return on investment (ROI) needs to be demonstrated through increased efficiency, reduced downtime, and improved product quality [11].

Finally, some companies take privacy and security issues very seriously. Real-time processing systems need to comply with privacy requirements and protect data. Protecting sensitive data needs a platform to build strong security measures such as encryption, access restrictions, etc. Additionally, continuous monitoring and regular security audits help identify and address vulnerabilities promptly and ensure that the system can withstand threats.

4 Conclusion

This paper reviews significant advantages and some challenges that it has to face right now in anomaly detection for manufacturing robots. The approach includes a detailed ML process from data collection to industrial deployment. The importance of Deep-Learning, CNN, DNN, and also YOLO algorithm is included. The results demonstrate the efficiency and accuracy of AI in identifying defective products. However, challenges such as cost and safety issues are also disadvantages of robotic anomaly detection. Future directions include improving model adaptation, ensuring seamless integration and enhancing data security.

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